Assimilation of precipitation-affected radiances in a WRF ensemble data assimilation system

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Motivation

the Global Precipitation Measurements (GPM) Mission will provide large amount of precipitation observations. It is a scientific challenge to best utilize precipitation data in weather and climate modeling, and hydrological applications

A WRF ensemble data assimilation system is developed to:

- explore the potential of using data assimilation techniques and cloud-resolving models to dynamically downscale satellite precipitation observations

- examine the problems unique to assimilating precipitation observations into a forecast system, such as

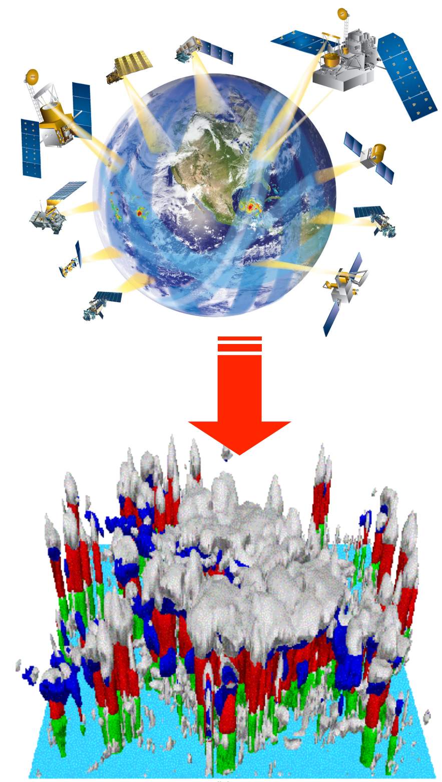
    -- prognostic hydrometeors in control variables
    -- background error covariance in precipitating region
    -- precipitation-affected radiance assimilation overland.

Key Words

Precipitation-affected
Satellite Observations

Cloud Resolving
forecast Model

Ensemble
data assimilation

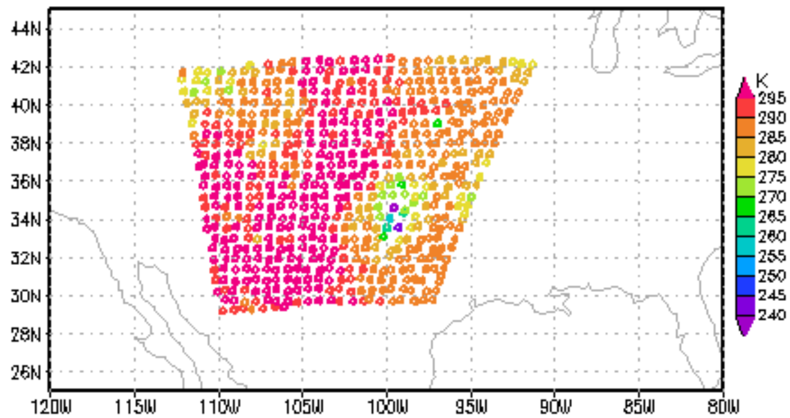


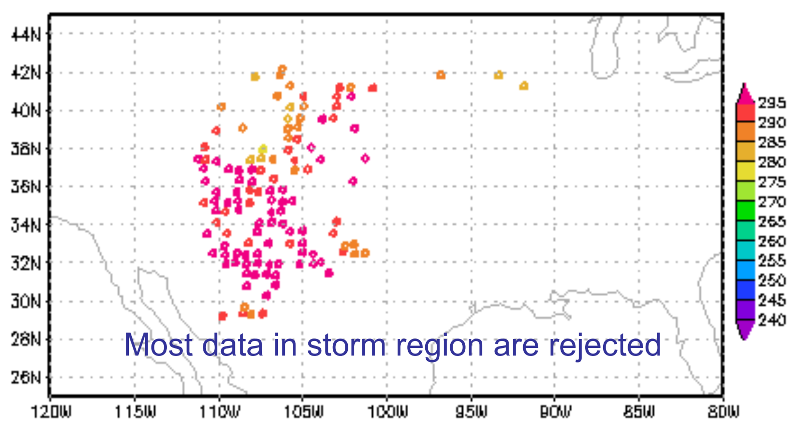
bring together the information from satellite precipitation data and model simulations to produce dynamic precipitation analysis

Precipitation-affected Satellite Observations

"clear sky" radiances
designed to observe moisture or temperature.
data in precipitation regions are not used.

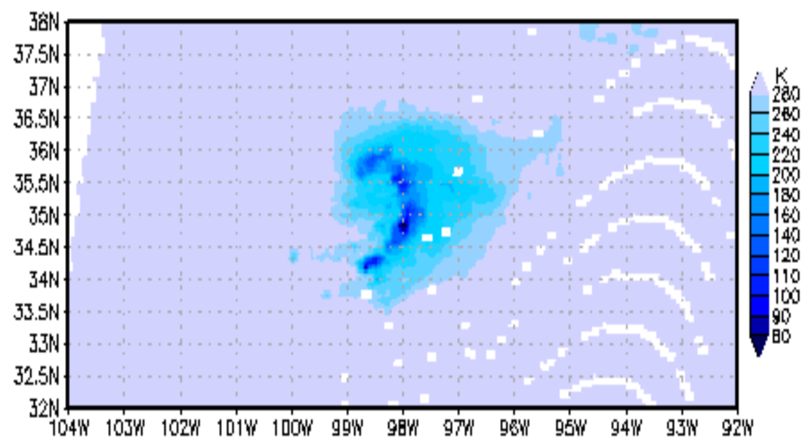
AMSU-B radiances (channel 1)





"Precipitation-affected" radiances
designed to observe precipitation.
Precipitation signals should be utilized to provide information in precipitation region

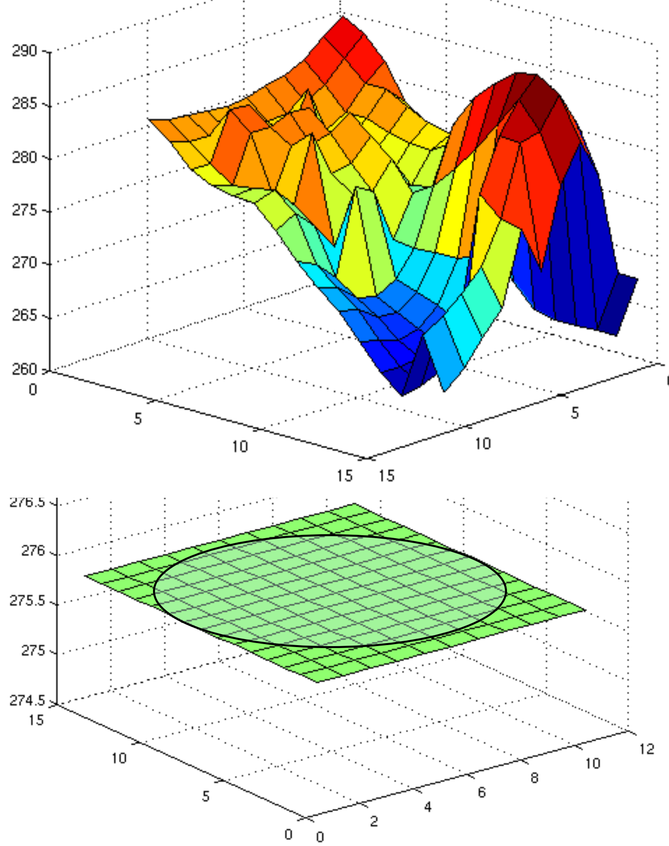
AMSR-E radiances at 89GHZ

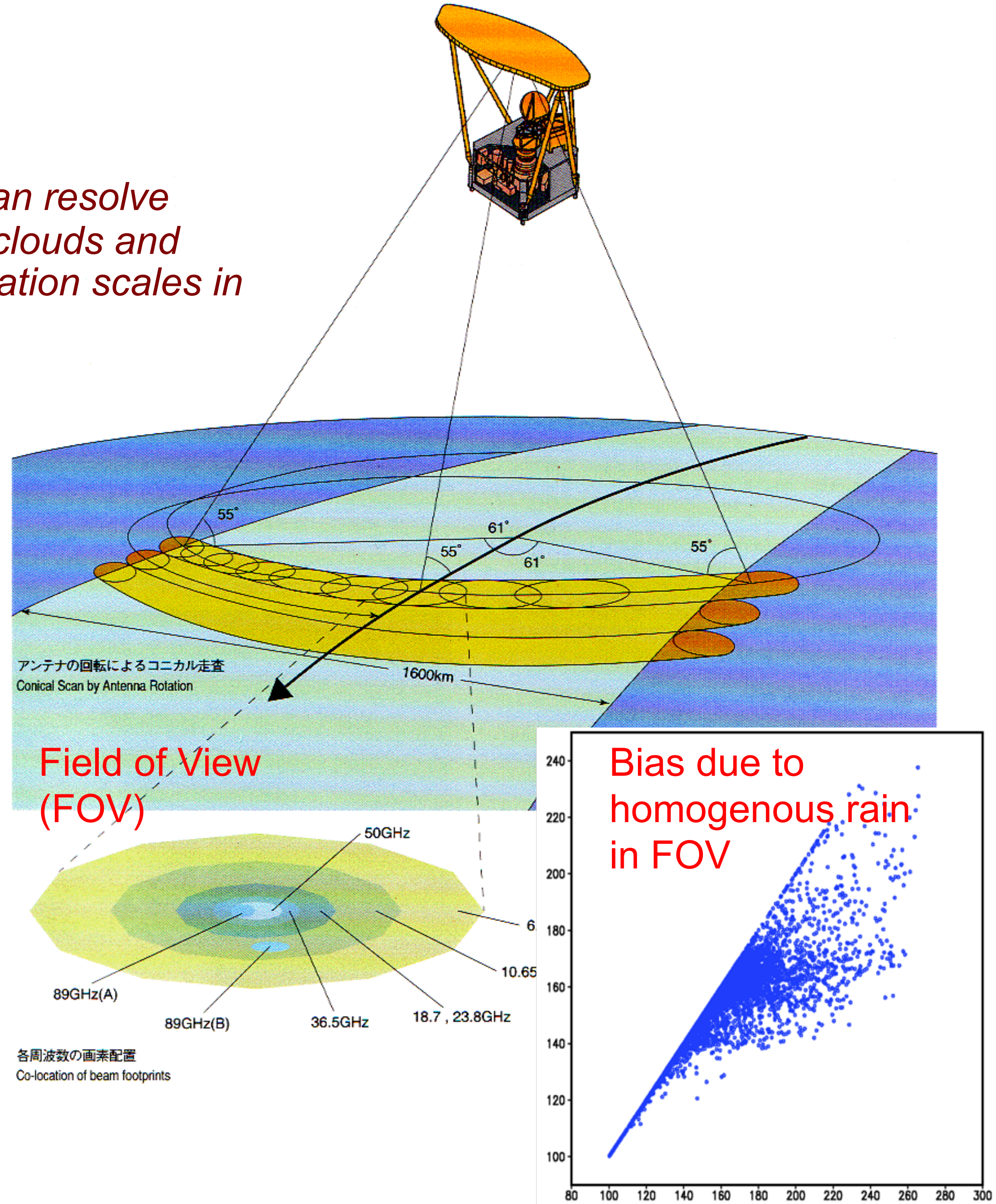


Cloud Resolving forecast Model

High resolution and microphysics can resolve finer-scale and larger variability of clouds and precipitation to better match observation scales in cloud/rain regions

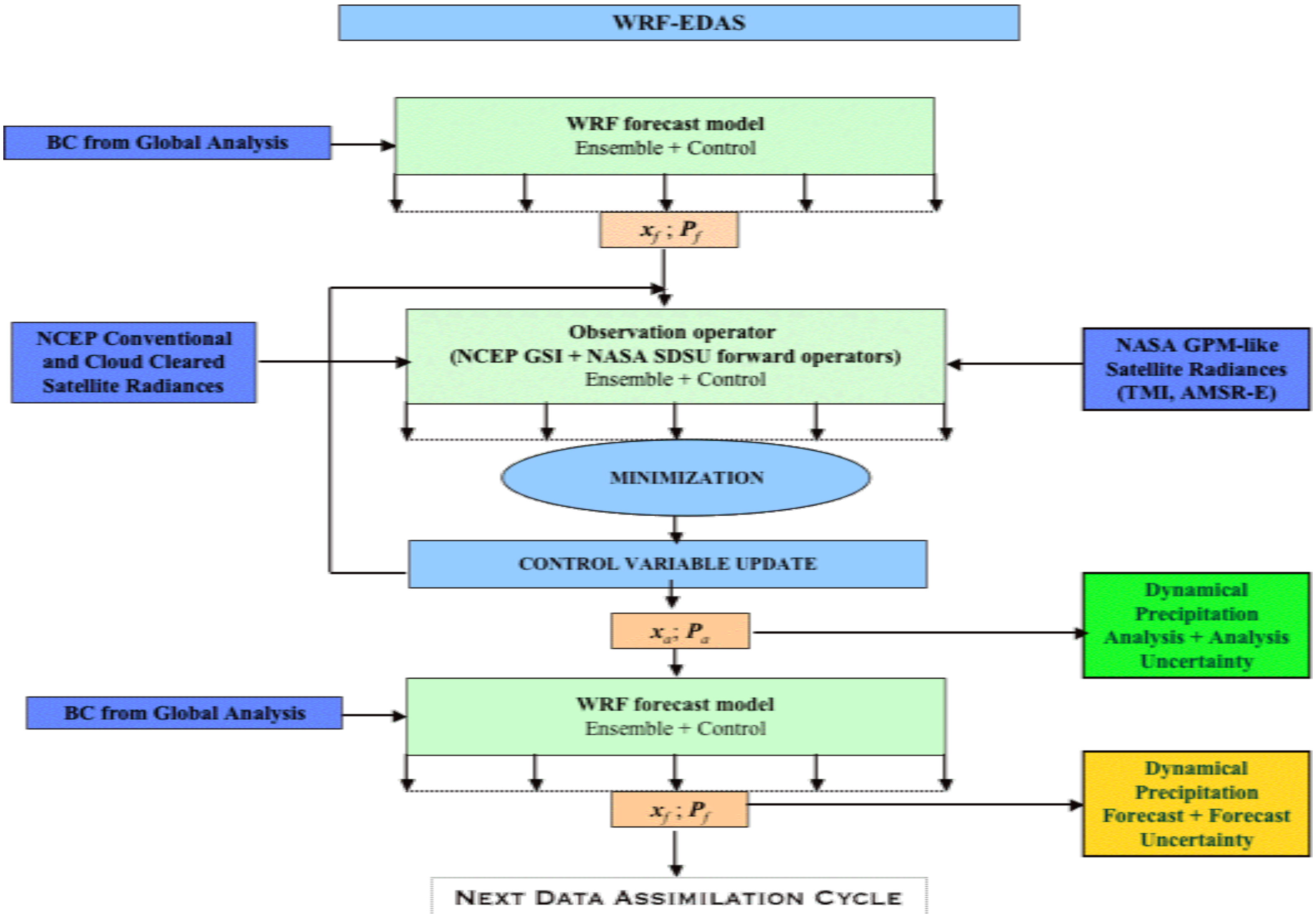
Simulated radiances in FOV





Ensemble data assimilation system

WRF-EDAS



WRF-EDAS in a nutshell

- *Model:* WRF provides 3h forecasts, with non-hydrostatic dynamics at 9KM to 1KM resolution in nested domains, and Goddard microphysics. Global analysis provides the forcing at the outer domain lateral boundaries

- *Observations:* precipitation-affected microwave brightness temperatures (TMI, AMSR-E), clear-sky sounder brightness temperatures (AMSU-A, -B, HIRS, MHS), and conventional data

- *Observation operators:* Non-linear cloud-resolving physics and radiance transfer models (without tangent linear models and adjoints)

- *Analysis control variables:* U-wind, V-wind, temperature, moisture, and hydrometeors (mixing ratio of rain, cloud, snow, ice and graupel)

- *Analysis algorithm:* maximum likelihood ensemble filter (Zupanski, 2005), a version of ensemble Kalman square-root filter, with a maximum likelihood solution as central analysis, and an unperturbed forecast as control forecast

- *Background error covariance*: state-dependent for all control variables, estimated and updated by ensemble forecasts and localization scheme, with 32 ensemble members

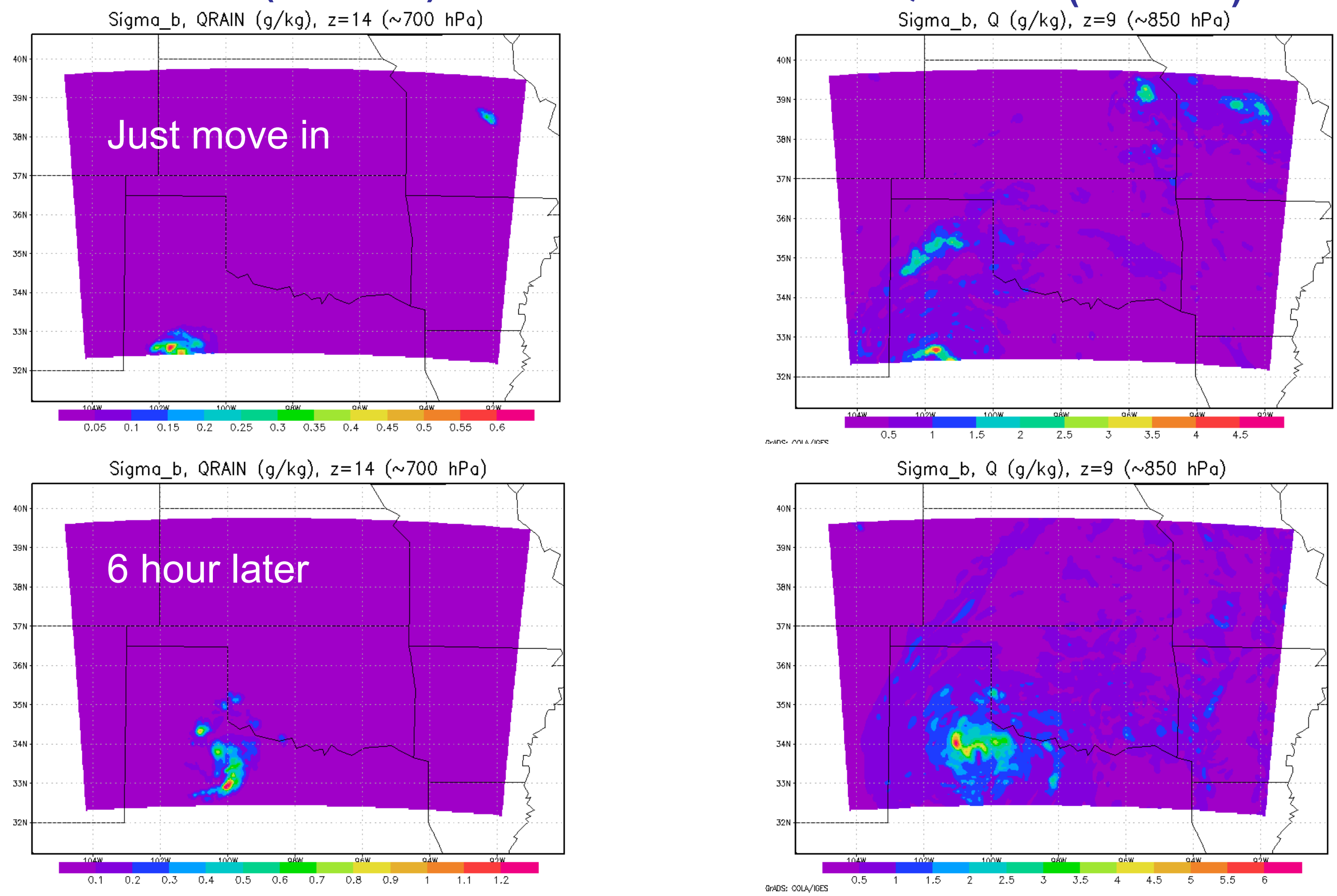
Background error covariance

State-dependent background error covariance

an example: storm Erin (2007) moving into the inner domain of WRF

background error standard deviations $\boldsymbol{\sigma}_b$ at 700 hPa and 850 hPa

QRAIN (700 hPa) | **QVAPOR (850 hPa)**

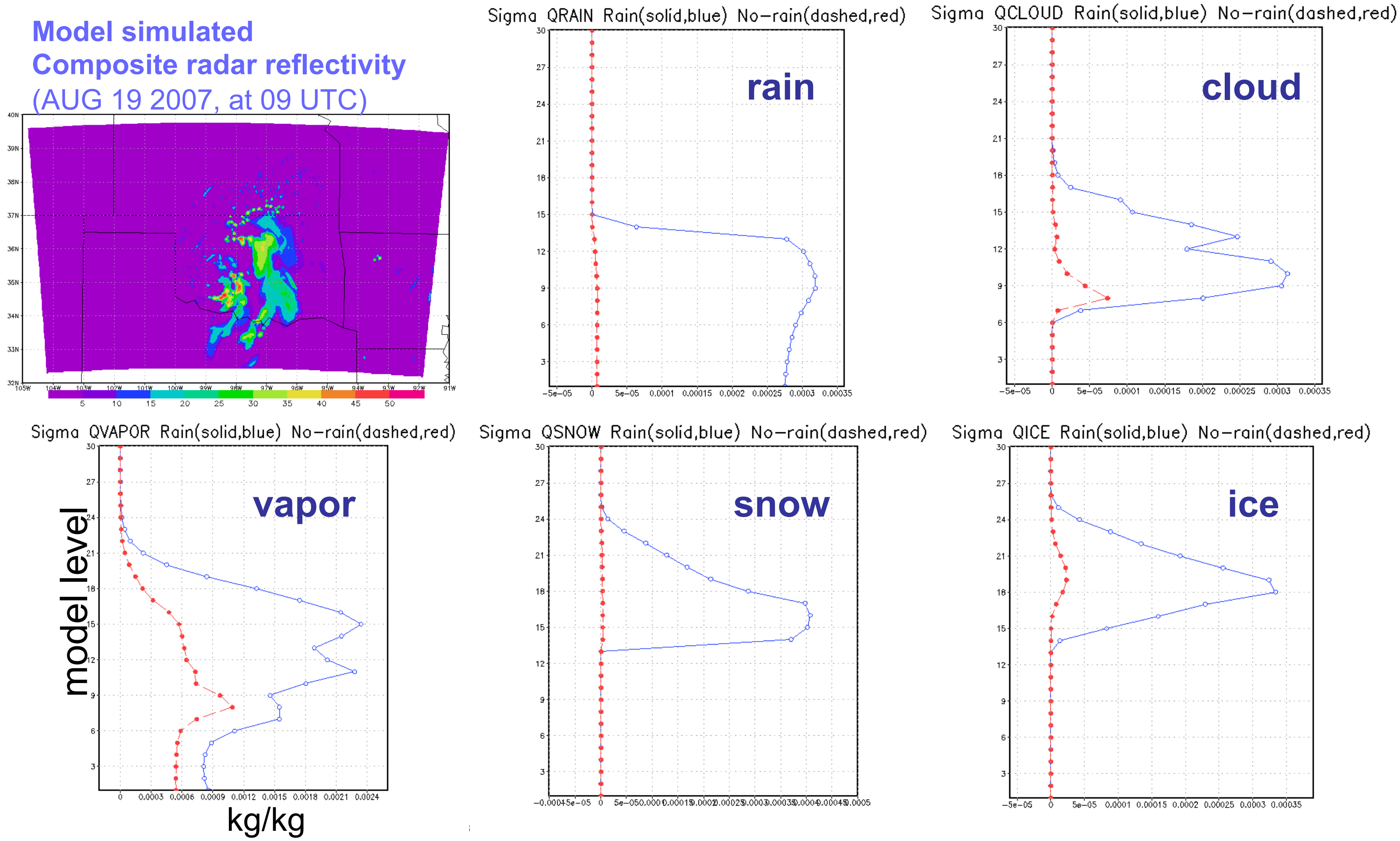


Temporal and spatial patterns of background error standard deviations are dependent on the storm location and dynamic structures

State-dependent background error covariance

an example: storm Erin (2007) in the inner domain of WRF

horizontally-averaged error standard deviations $\boldsymbol{\sigma}_b$ in raining (Blue) and no-rain (Red) area

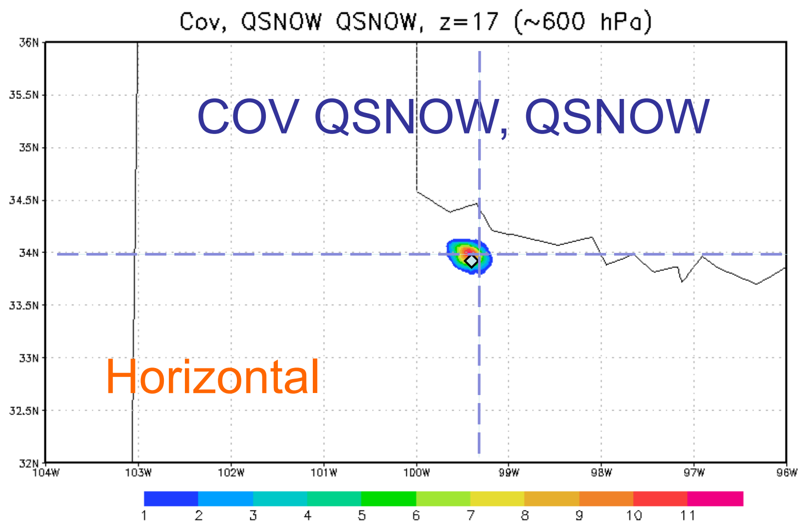


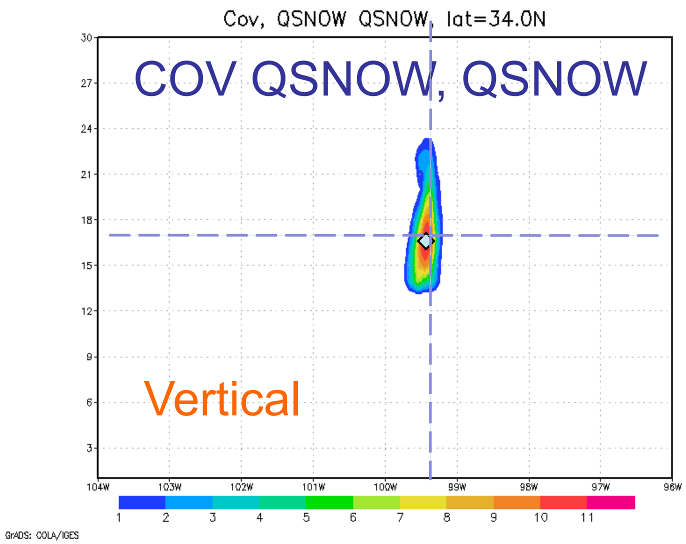
Much larger background error standard deviations in the storm region allow more significant corrections from observations via analysis

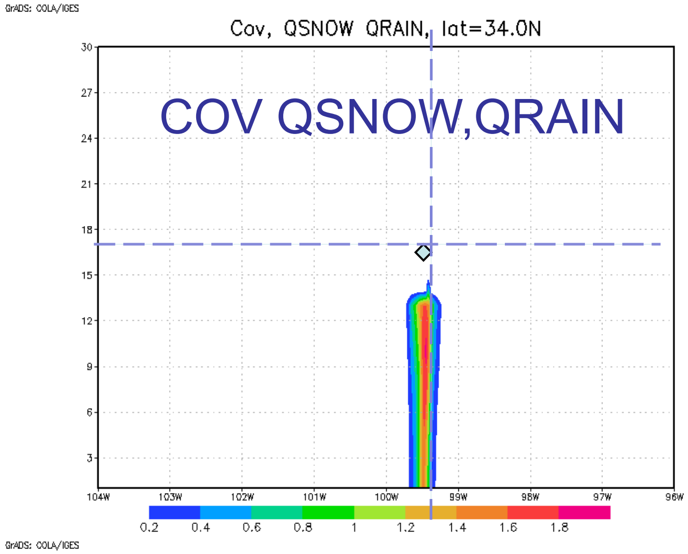
background error cross-covariance

(an example: analysis response to one-point "observation" of QSNOW at 600 hPa)

(valid Aug 19, 2007, at 03UTC)







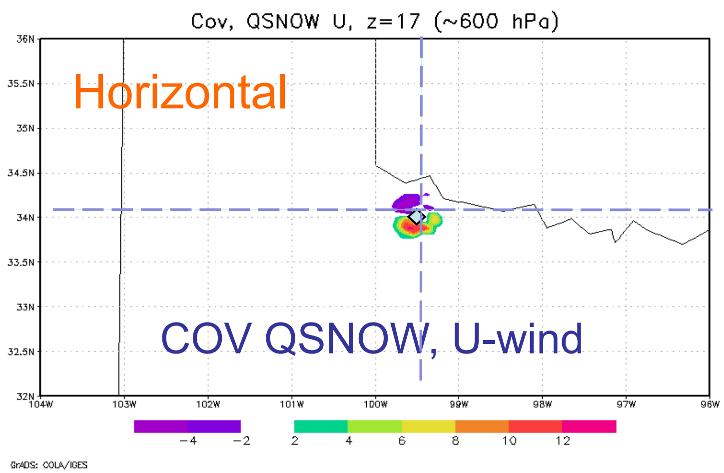
- local impact on the same variable (Qsnow)
- localized column impact on Qrain

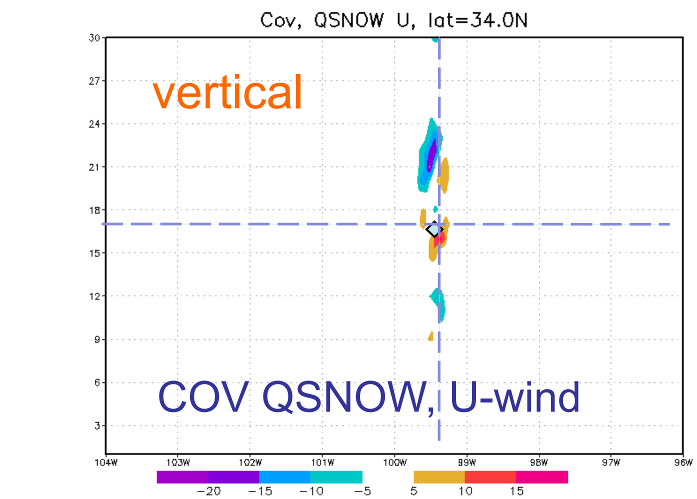
•Background error cross-covariance spreads information of an observation on one variable at one location to the neighborhood and to other variables.

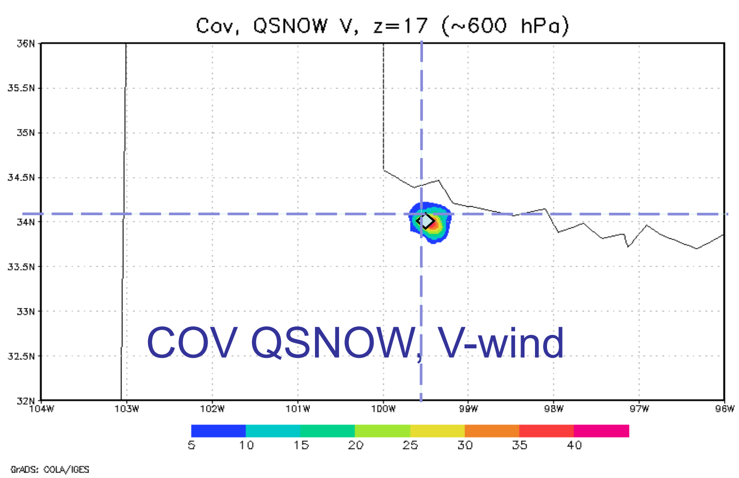
•An radiance observation senses scattering from snow content at one location, this information can be used to correct the snow content nearby, and to correct rain content in the column below.

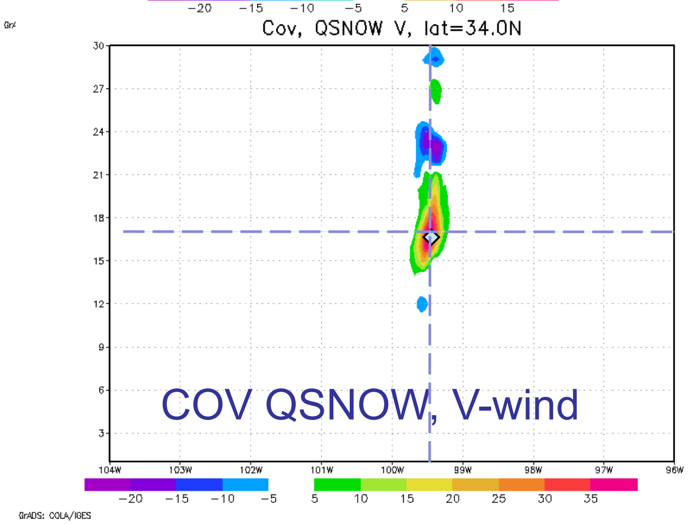
Background error cross-covariance

(WIND analysis response to one-point "observation" of QSNOW at 600 hPa)







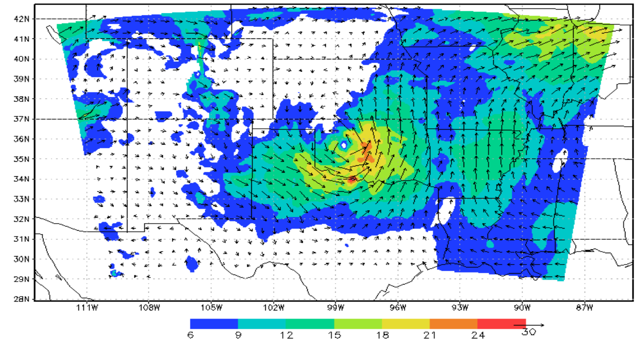


An radiance observation on snow content can have impact on wind field thanks to the error cross-covariance between snow and wind

An example of radiance observation impact to wind via assimilation of AMSR-E brightness temperature

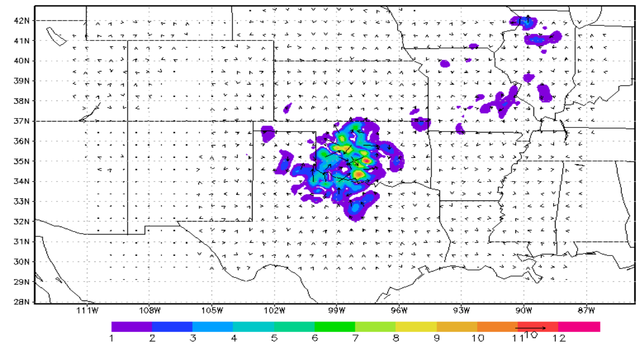
Wind at 700mb
First Guess

(a)



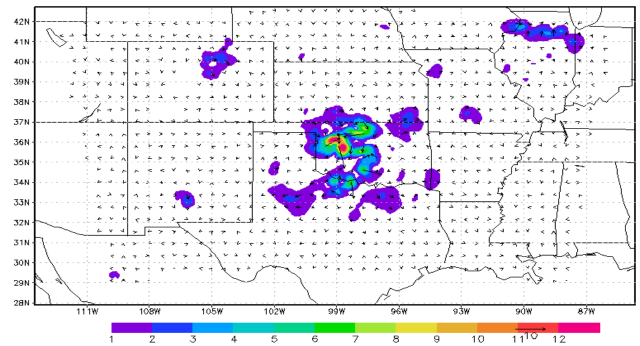
wind increments
due to AMSR-E data
(observation of radiance)

(b)



wind increments
due to conventional data
(observation of wind)

(c)

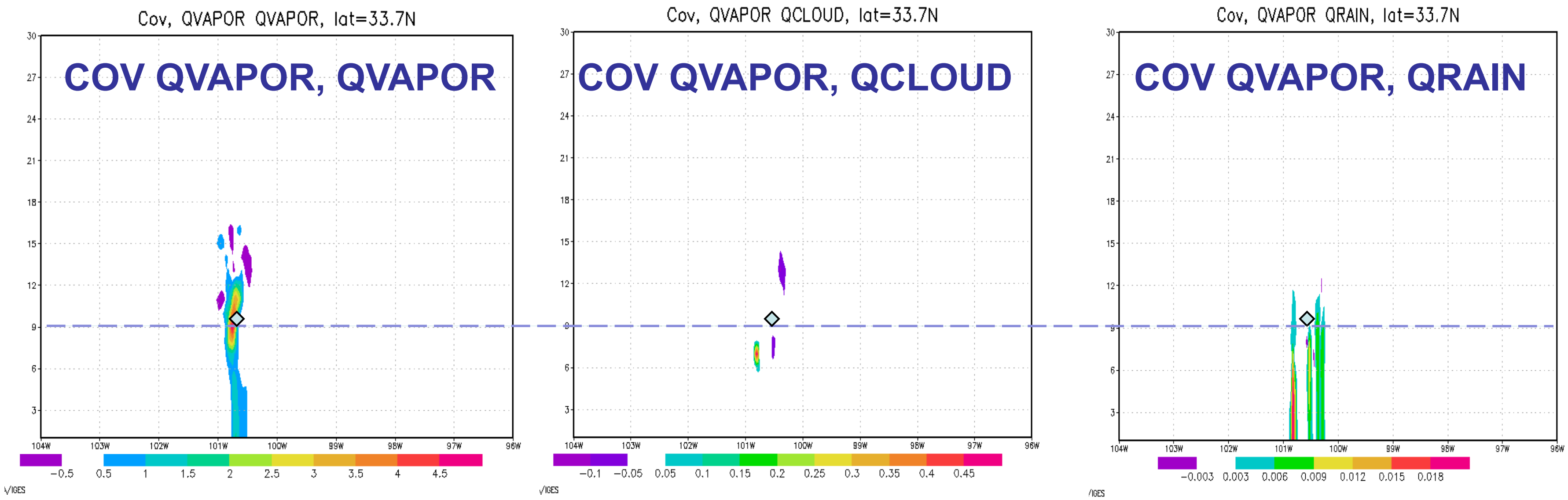


The positive radiance data impact to wind is confirmed by the similarity between increments due to radiance data and increments due to wind observations.

background error cross-covariance

(analysis response to one-point "observation" of QVAPOR at 850 hPa)

vertical



In this case of a strong storm overland, the error cross-covariance is weak between vapor and cloud water, but is more substantial between vapor and rain water at the levels below.

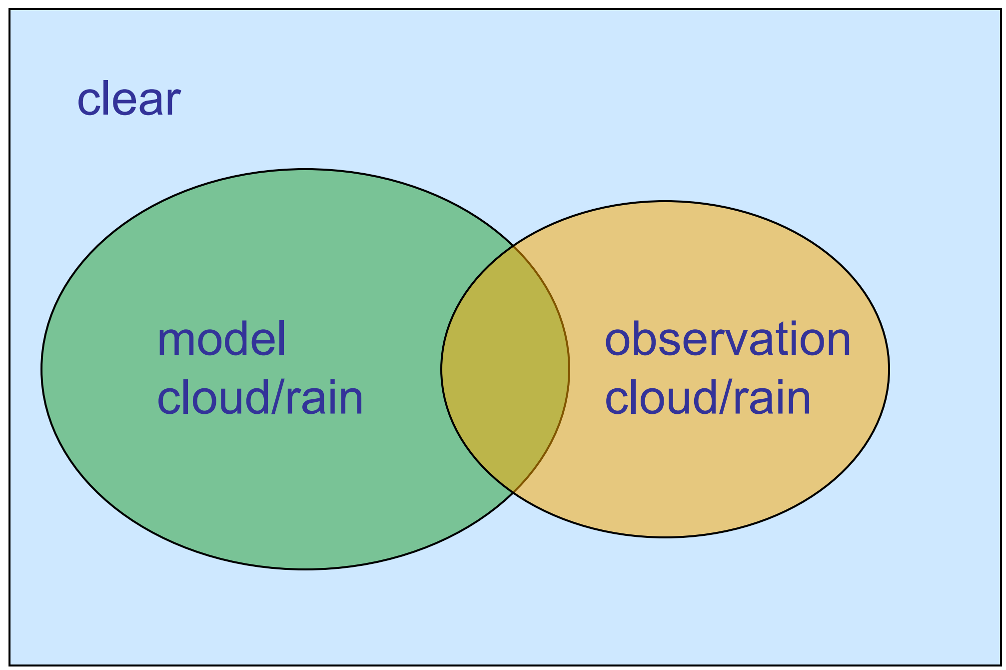
Observations

Dealing with precipitation-affected satellite observations in WRF-EDAS

- *Is it raining or not?   Model and observation often do not agree*
- *Is that a real precipitation signal? Land surface can have interference*

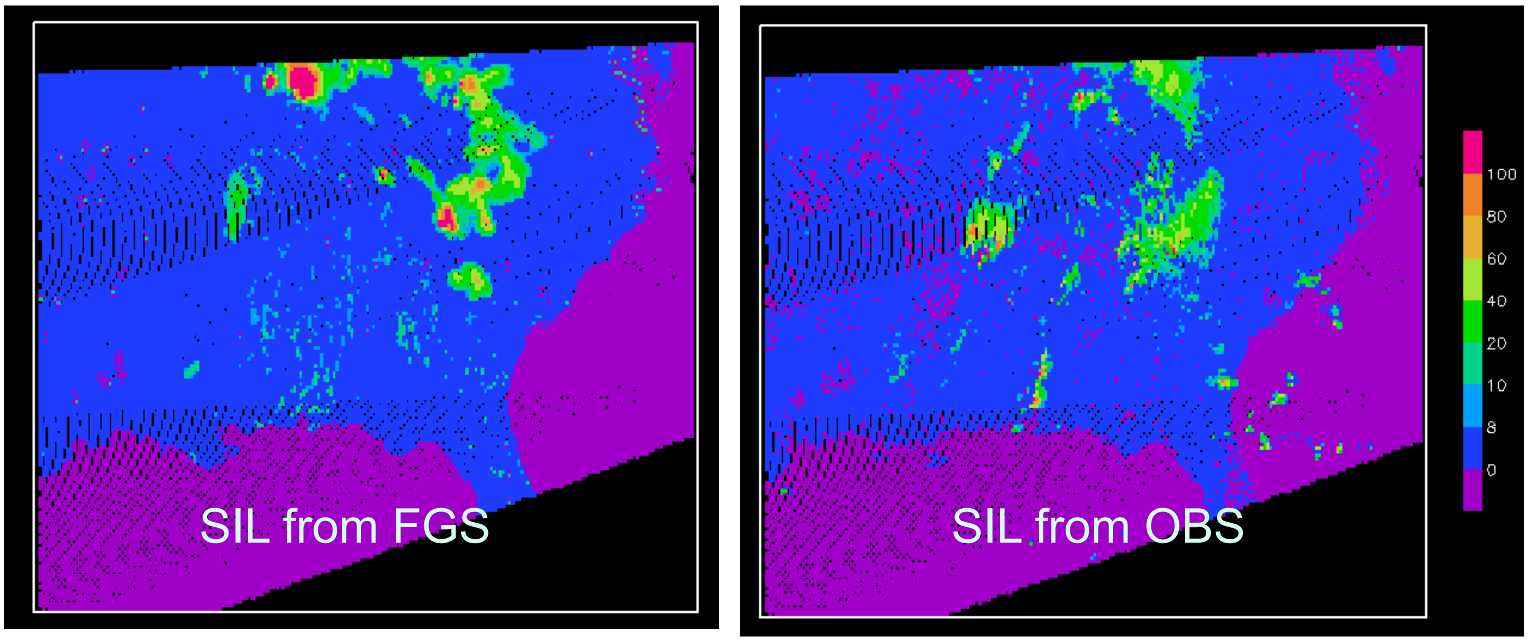
data selection
quality control
bias correction

Classification diagram



Data selection based on Scattering Index

Scattering Index (land)= f(Tb_19v, 21v, 85v)
parameter values from GPROF retrieval algorithms



✓*a piece of data is selected if the scattering index >10K, either SIL from first guess or from observation*
✓*only channels sensing scattering are selected when overland*
✓*a piece of data is rejected if the innovation is larger than 3 σ_0*

Bias correction for precipitation-affected radiance

Biases in radiance innovations are mainly caused by systematic errors in WRF inputs to RTM

- biased skin temperature or other surface conditions
- excessive snow or ice content
- excessive precipitation near boundaries
- …

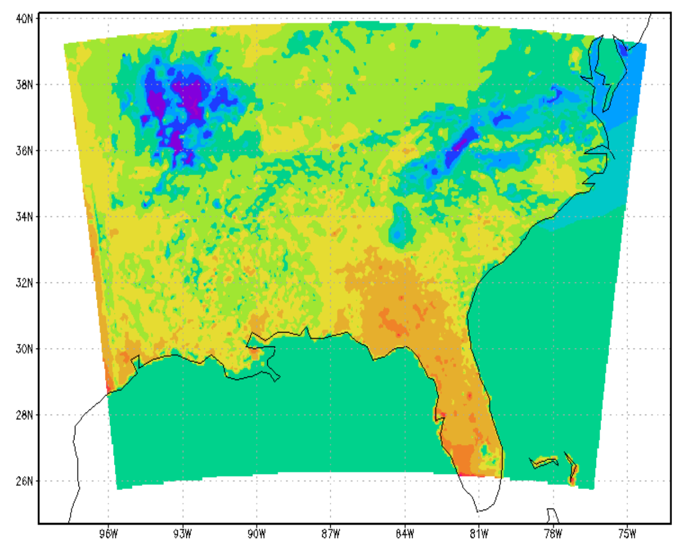
$$y = H(x_t) + B(\beta) + \varepsilon$$

$$B(\beta) = \sum_{i=1}^{N} \beta_i p_i$$

Need to find suitable predictors (p), build parameter (β) estimation and online bias correction into the analysis.

For instance, will use NESDIS skin temperature retrievals to asses WRF skin temperature, and develop a bias correction overland with skin temperature as a predictor

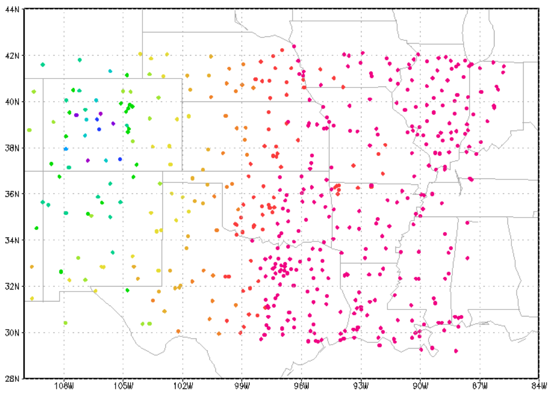
WRF skin temperature
Input to RTM 2009-09-19-18z

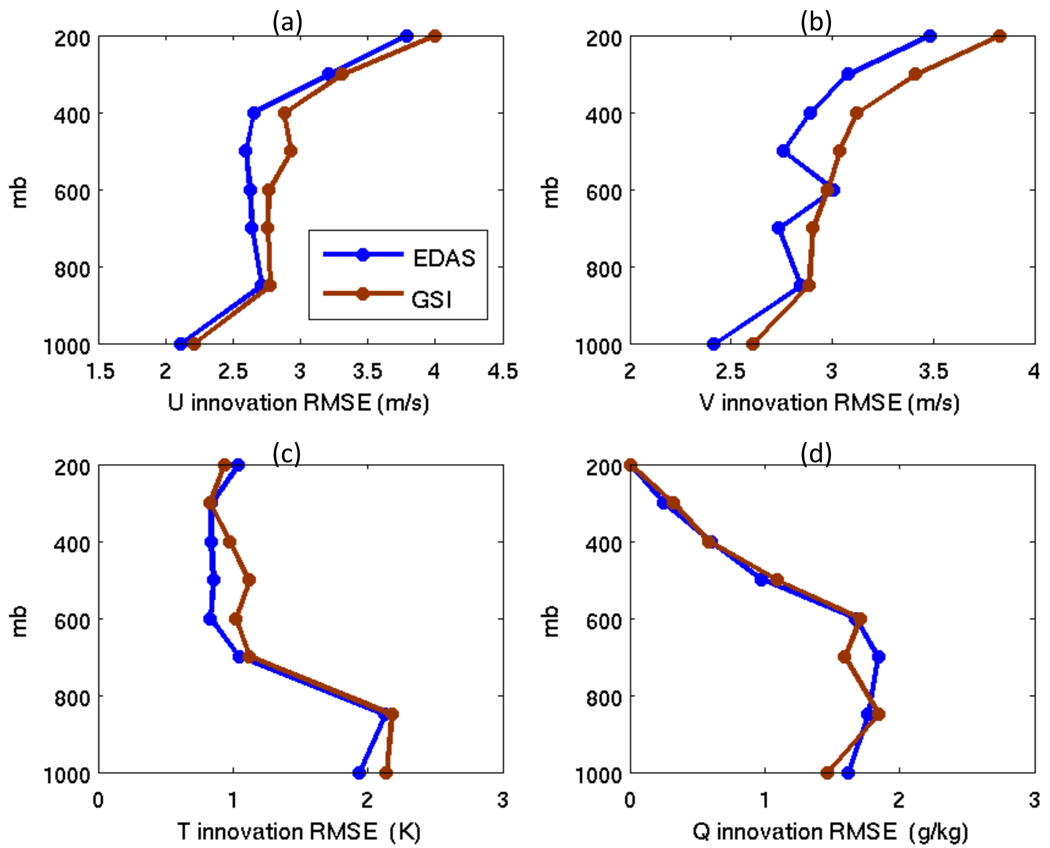


Assimilation of in-situ observations and clear-sky radiances to constrain the dynamical environment in the domain

Forecast Errors in U, V, T, and Q

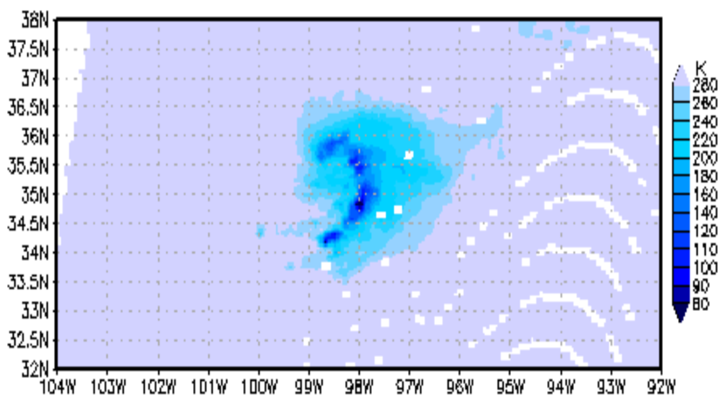
Ground-based observations in the domain





Assimilation of precipitation-affected radiances in the storm region

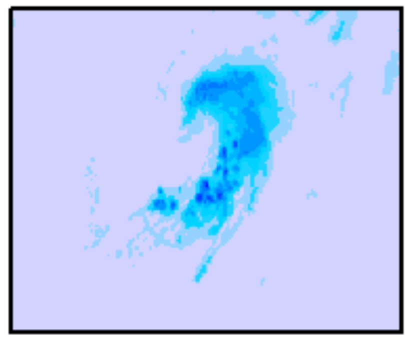
AMSR-E observations
in the storm region



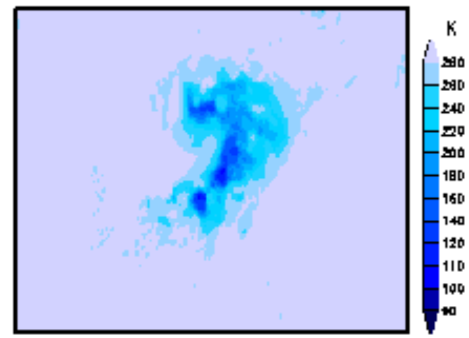
Assimilation of AMSR-E 89GHZ radiance

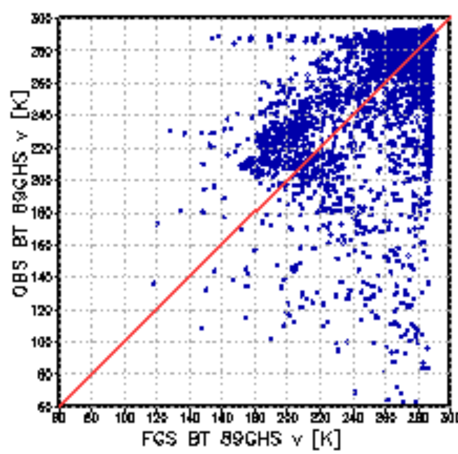
2007/08/18/09z
at 3 KM resolution (inner domain)

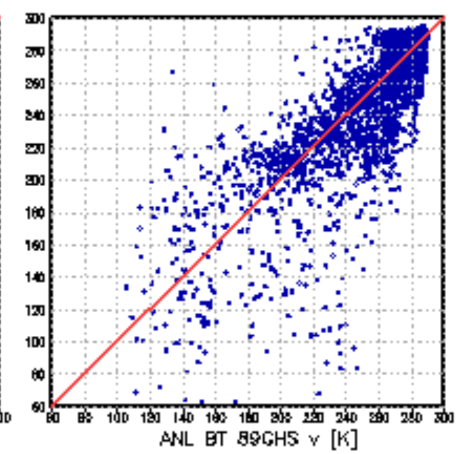
First guess



Analysis



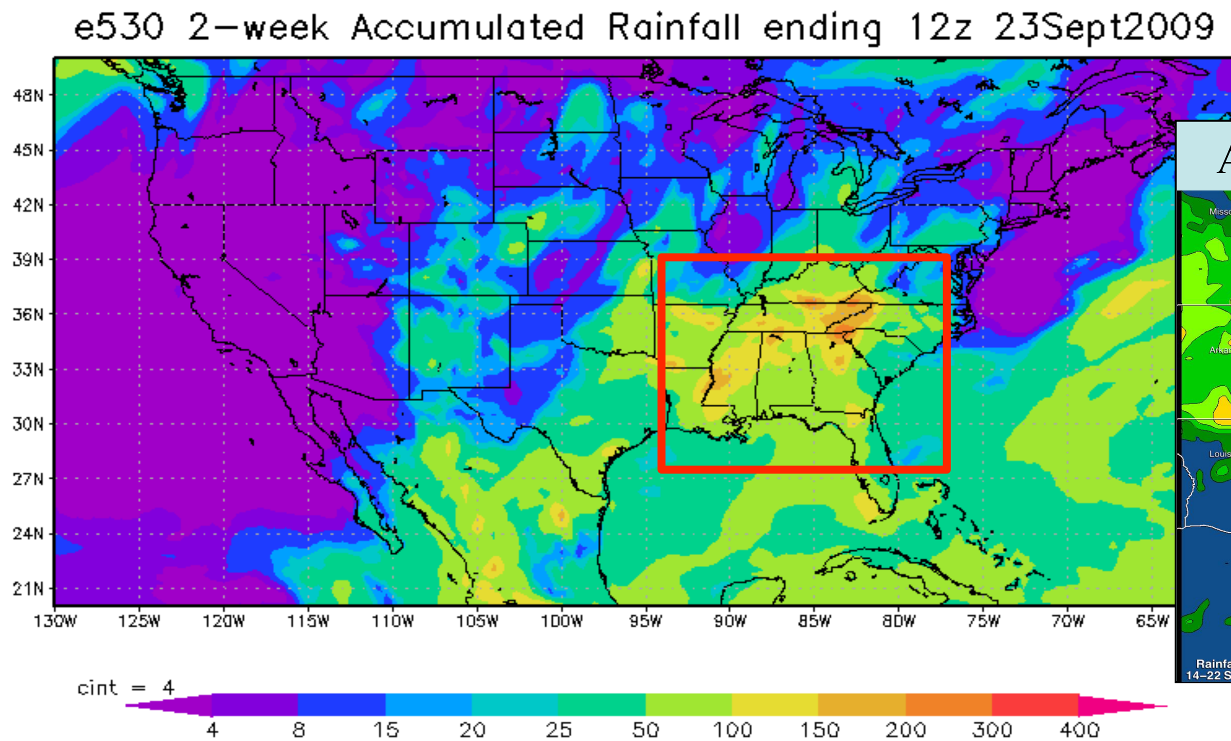


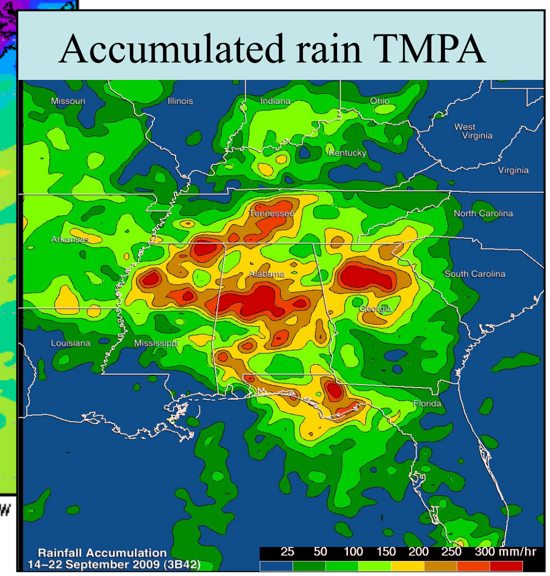


An assimilation experiment using precipitation-affected microwave radiances

The southeast heavy rain event in September 2009

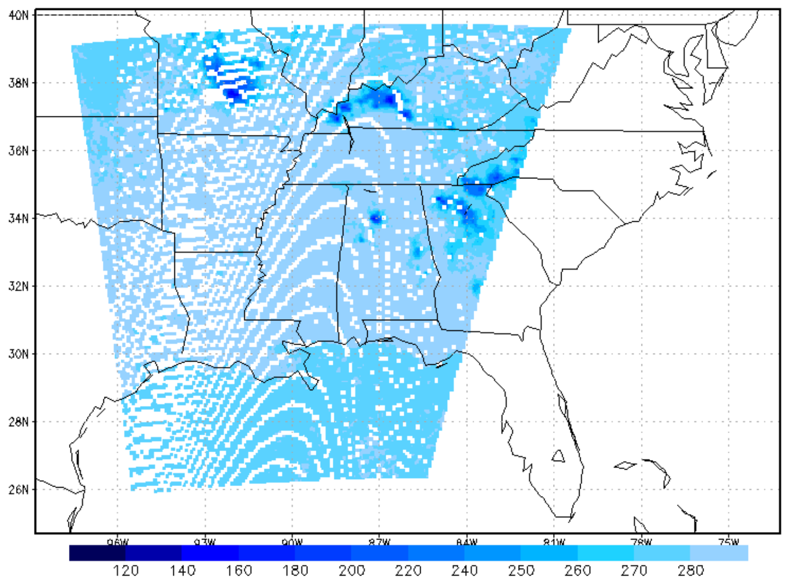
NASA-GSFC global 3DVar analysis accumulated rain



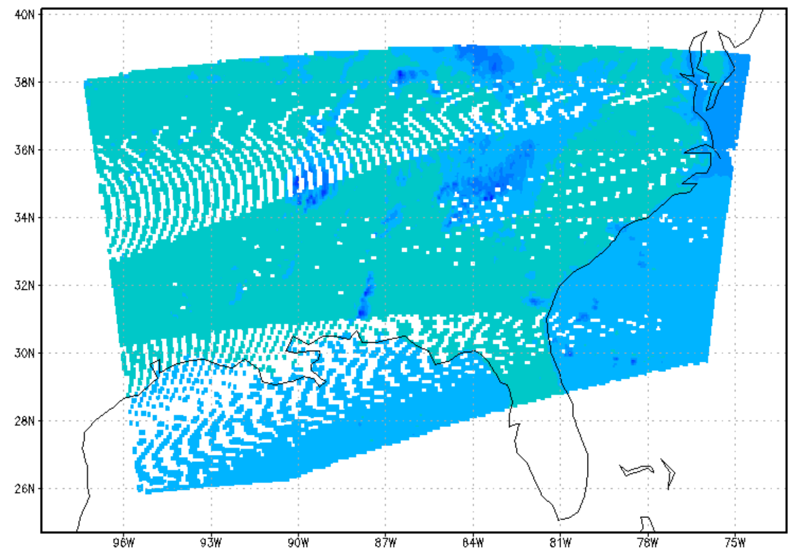


WRF-EDAS assimilated data available in the domain

AMSR-E observations
09z 9/20/2009
(89GHZ V)

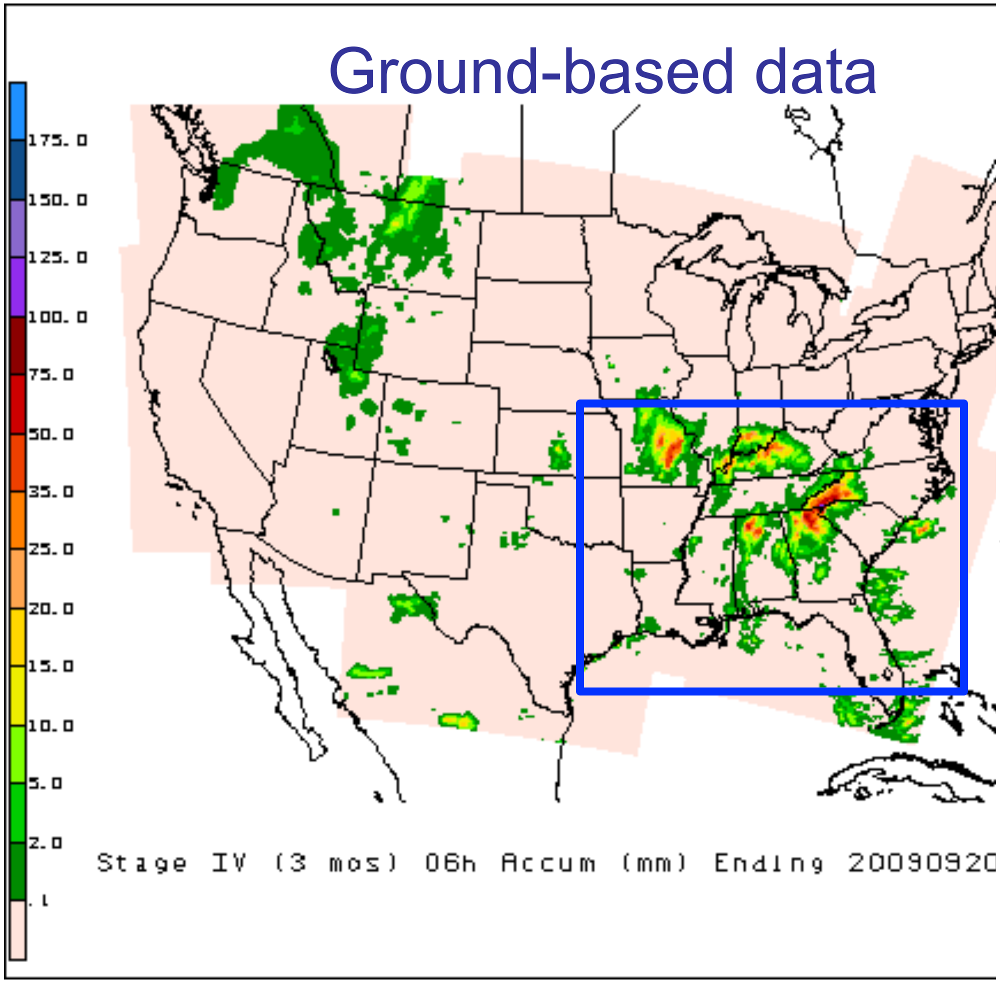


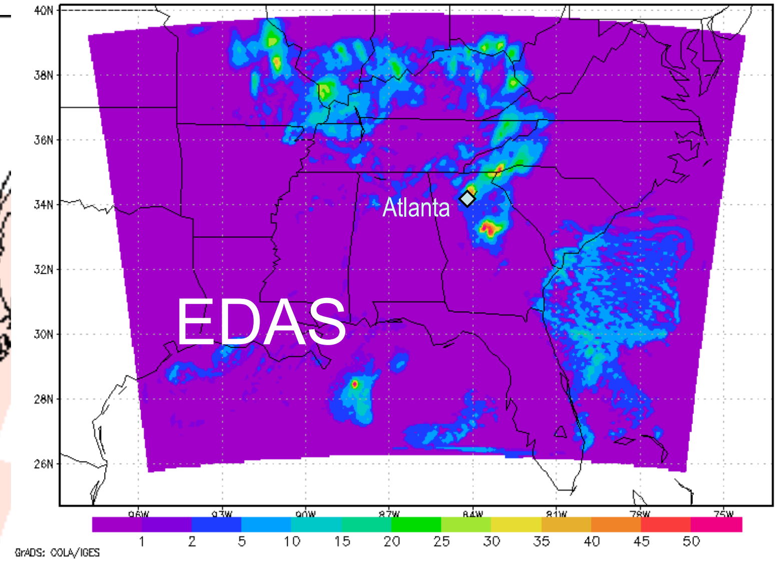
TMI observations
15z 9/20/2009
(85GHZ V)

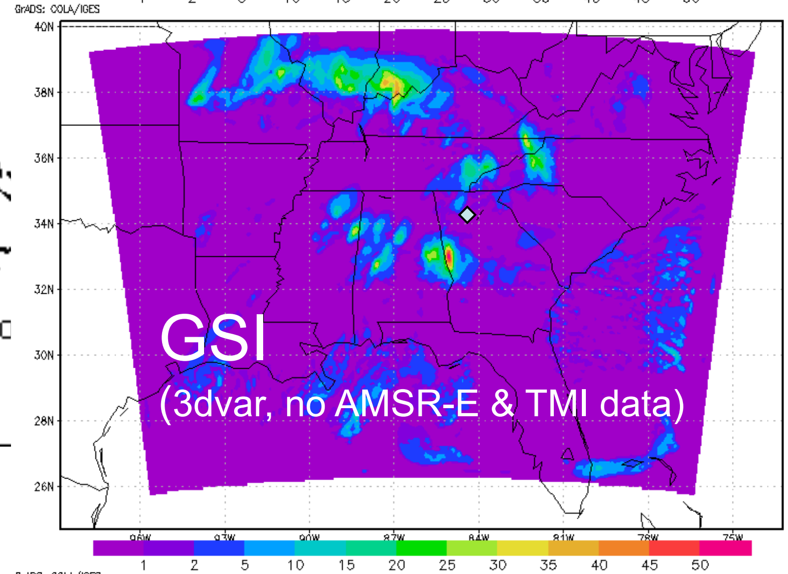


About 40% of time there are either AMSR-E or TMI data covering the domain. GPM will increase the temporal coverage significantly.

6h Accumulated rain forecast ending 2009092012z



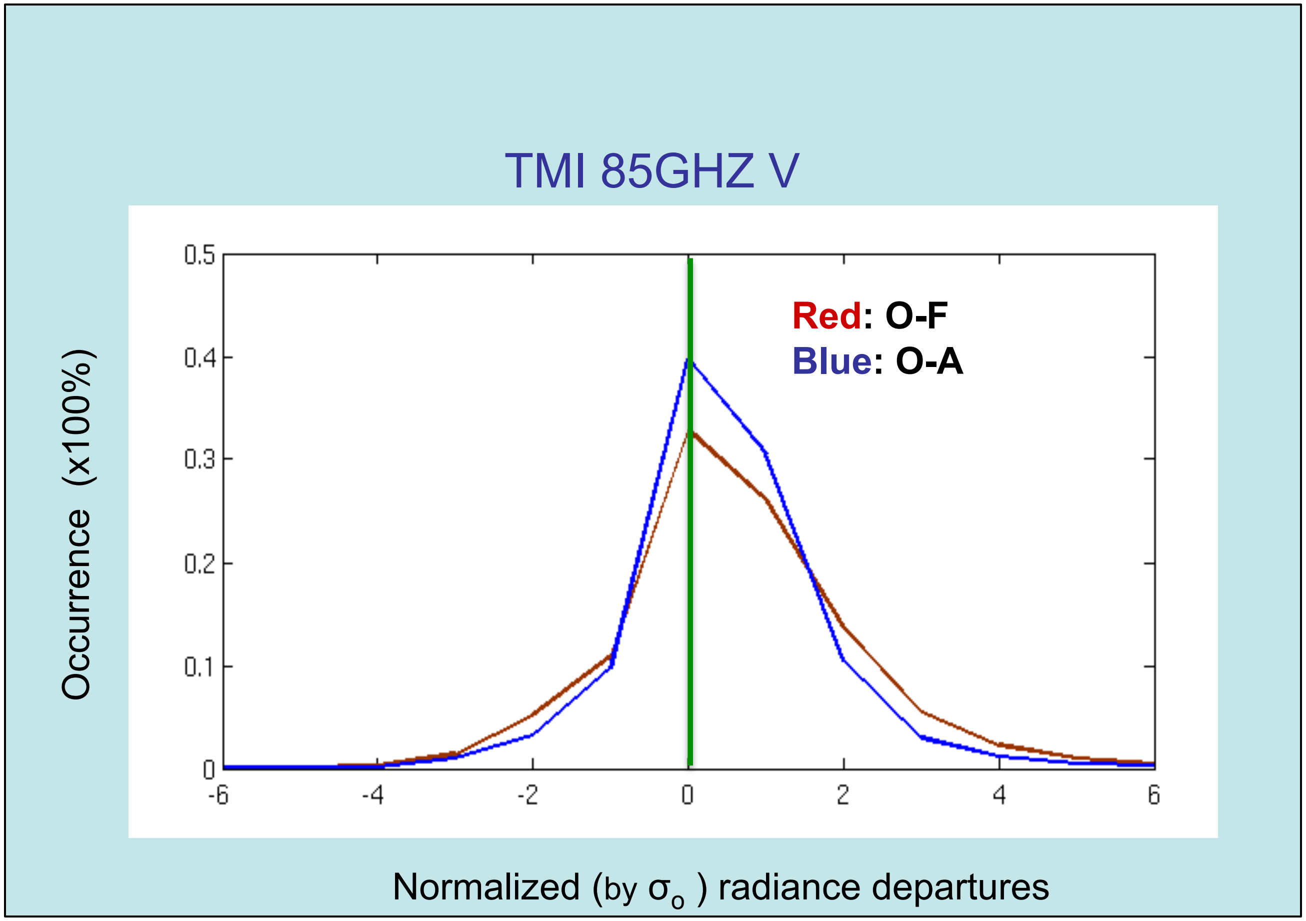




Atlanta metropolitan area was flooded

distribution of radiance innovations in rain regions over land

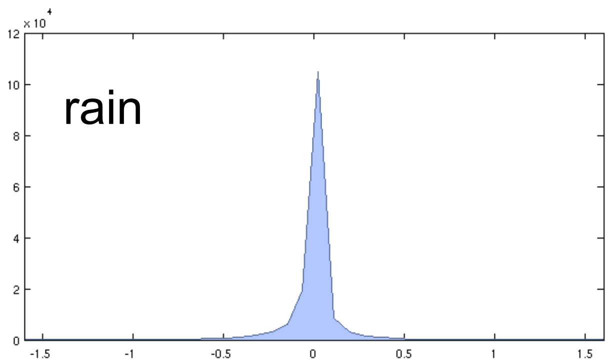
(collection from 80 cycles of assimilation)

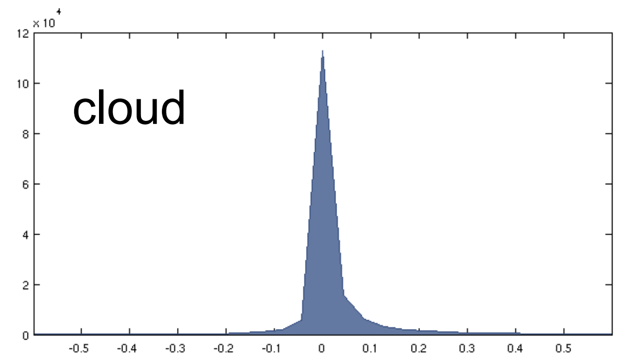


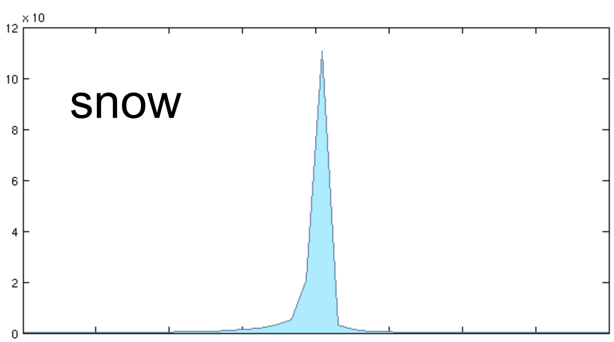
✓Departure reduced ?
✓Gaussian ?
✓Bias?

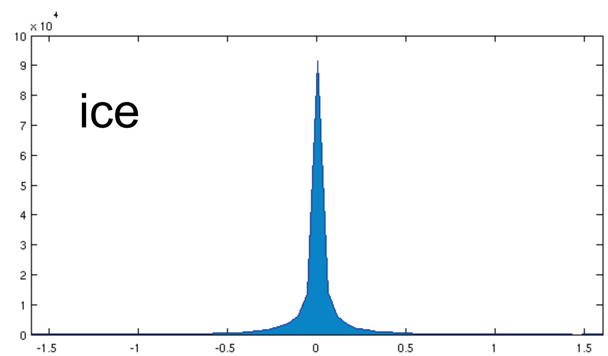
Distribution of hydrometeor analysis Increments

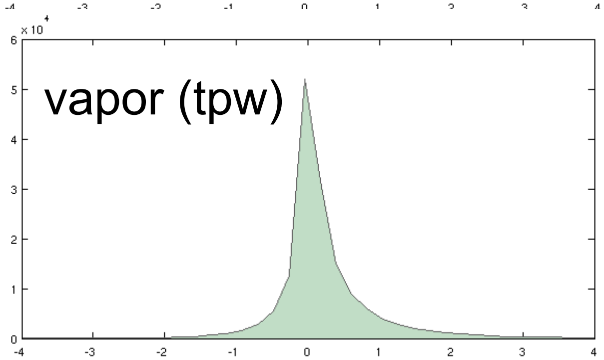
(shown in vertically integrated water paths)





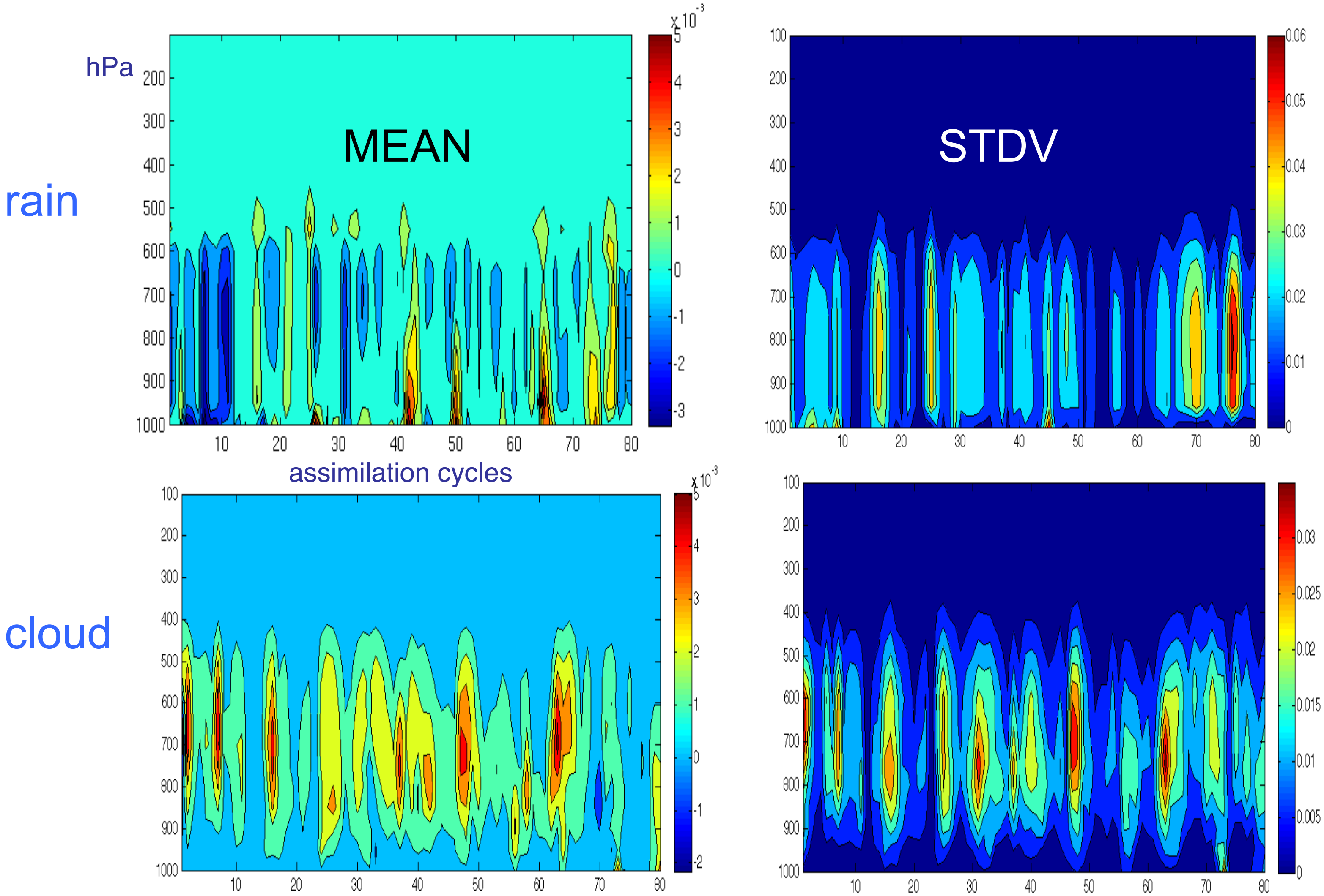






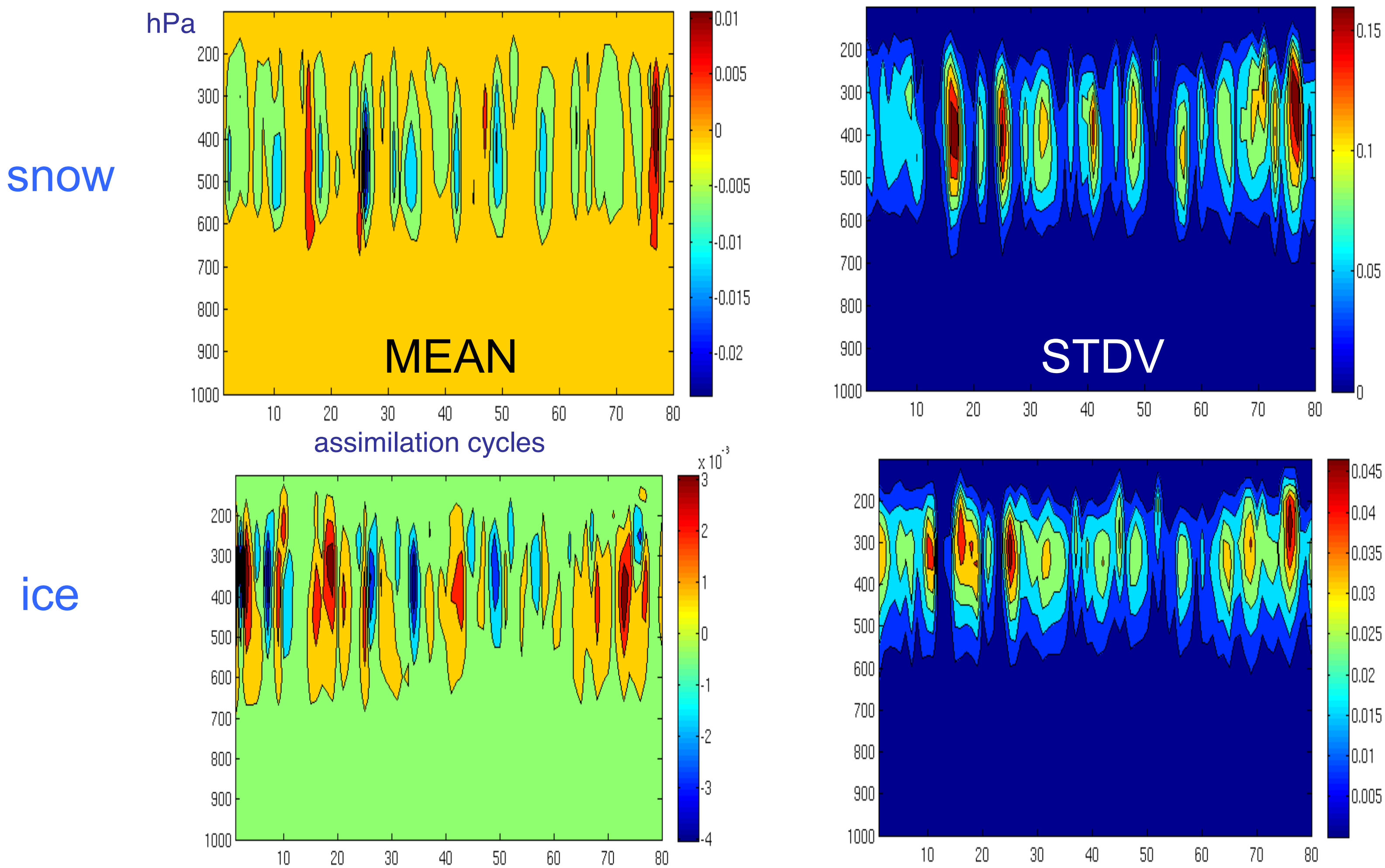
Check the analysis error distribution:
Gaussian ?
Standard deviation?
Bias?

Time series
Hydrometeor analysis increments, horizontally-averaged



Monitoring the analysis corrections to hydrometeor vertical structures due to assimilating brightness temperatures

Time series
Hydrometeor analysis increments, horizontally-averaged

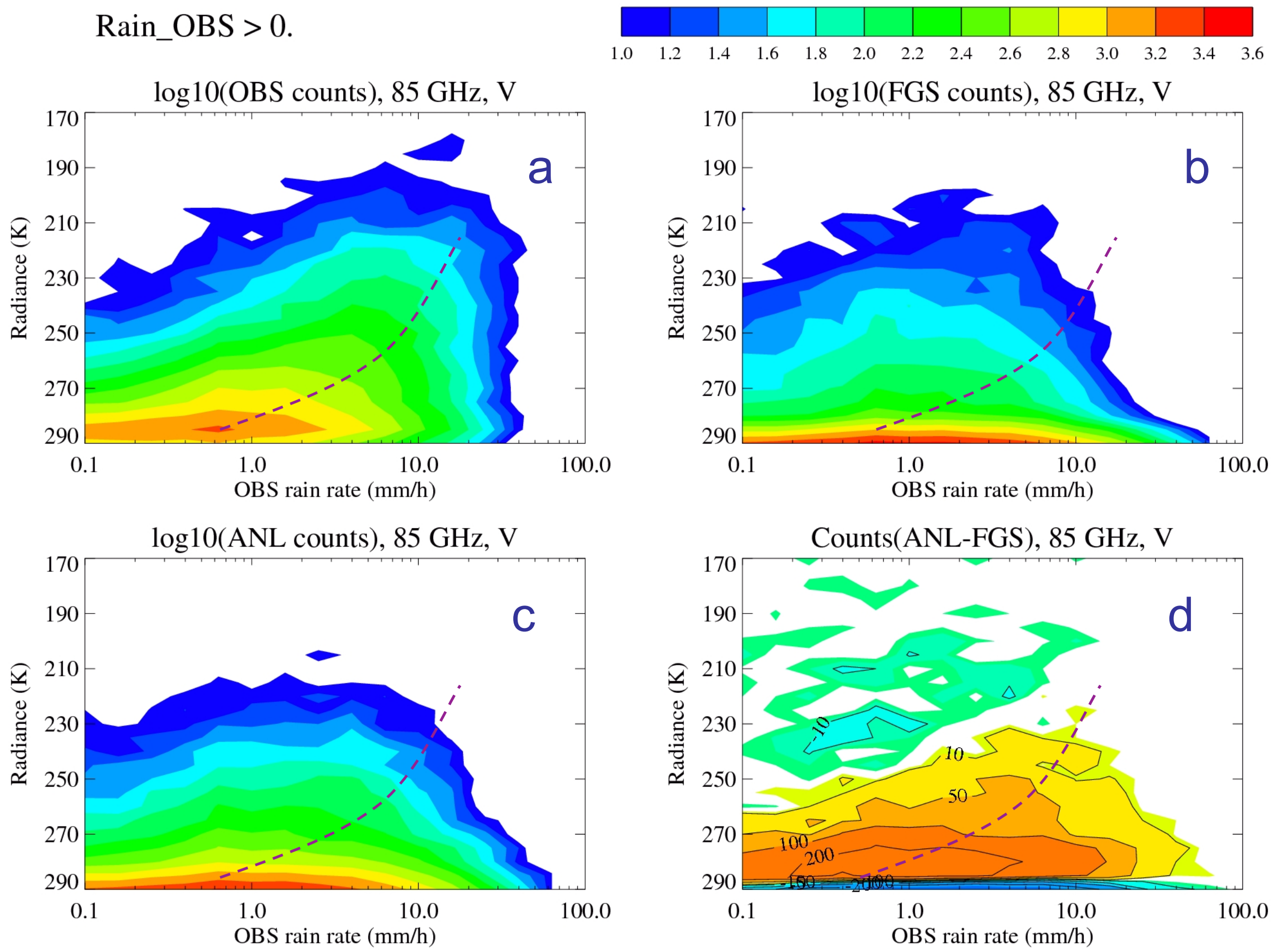


Analyses mostly modify total column amplitudes, not much alter profile shapes.
Little information in microwave BT on detailed vertical distribution
Observation information spread vertically according to error cross-covariance

Connection between microwave radiances and surface rain :

Use NCEP Stage IV surface rain data to examine assimilation results

Joint histogram of observed surface rain-rates and brightness temperatures



There is ambiguity in how BT 85GHz corresponds to surface rain-rates (illustrated by (a)).
Assimilation of BT improves the hydrometeors in raining areas observed by surface measurements (d)

Connection between precipitating clouds and surface rain :

Use NCEP Stage IV surface rain data to examine assimilation results

Joint histogram of observed surface rain-rates and different cloud tops

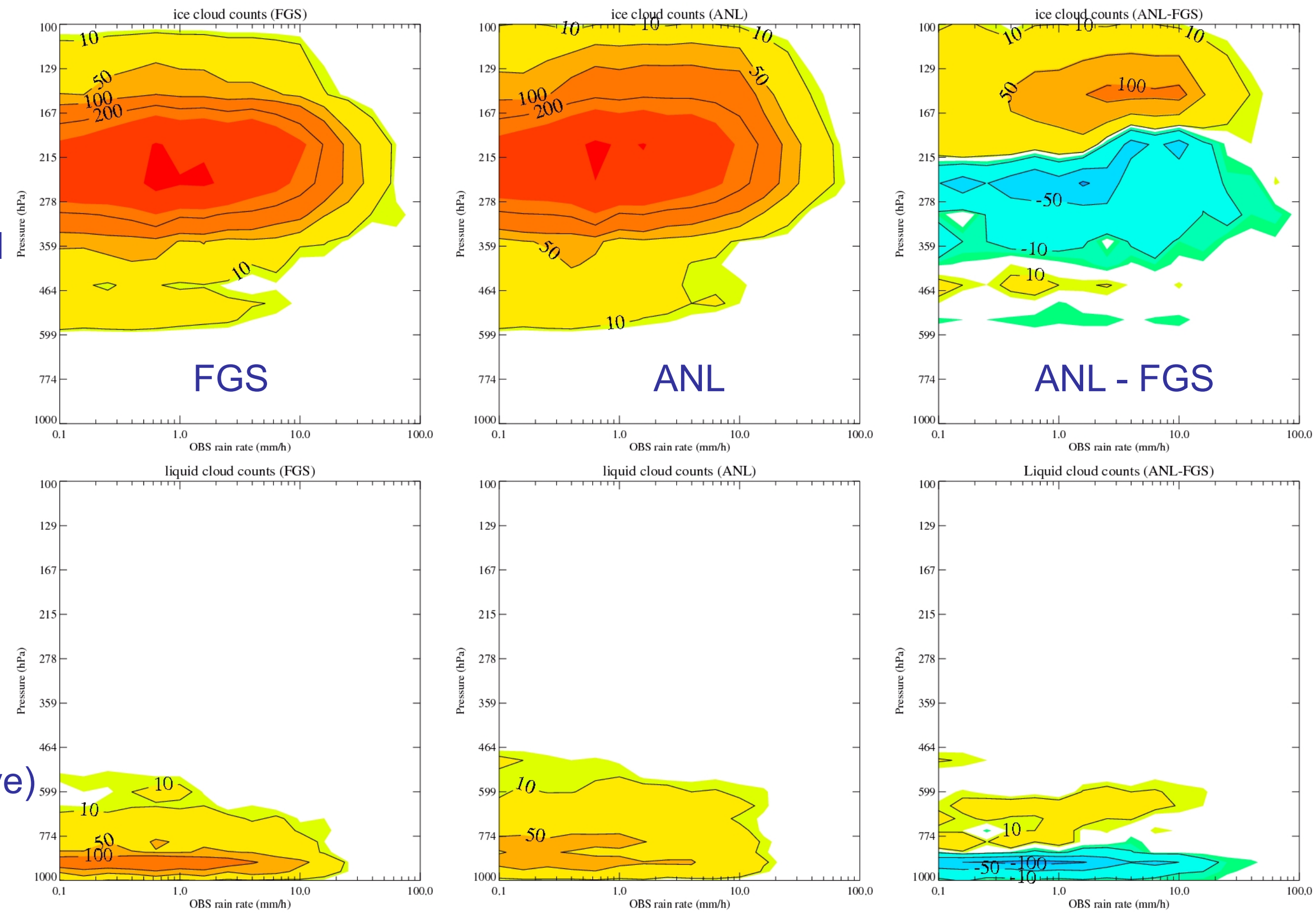
For areas where rain_OBS > 0

ice clouds

(counts on the top level with ice content)

liquid clouds

(counts on the top level with no ice content above)

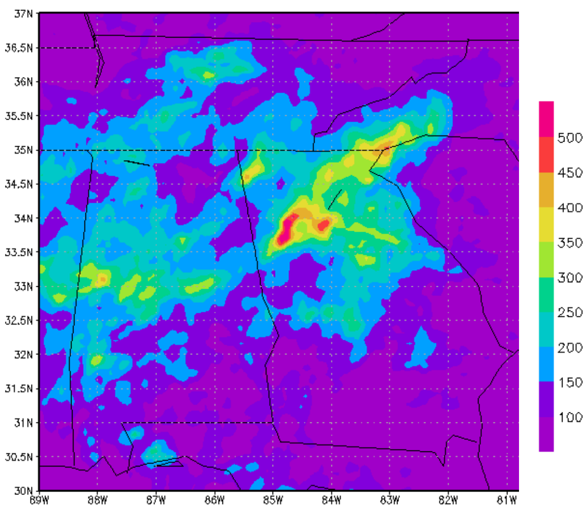


Assimilating BT in raining area statistically increased cloud population with higher cloud top

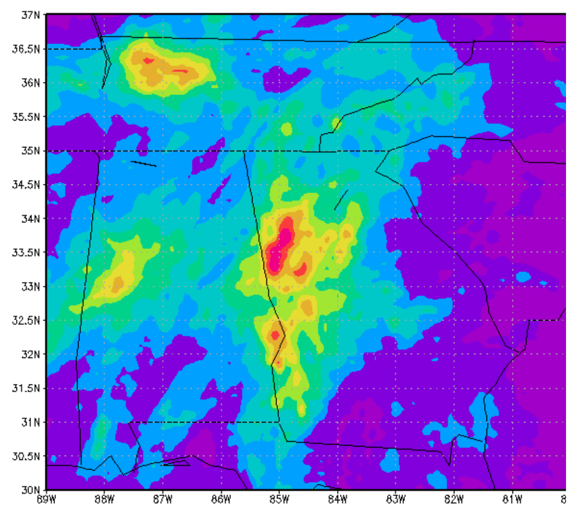
Surface precipitation short-term forecasts verification

Accumulated rain during 15-22 September 2009 in the Southeast flood region

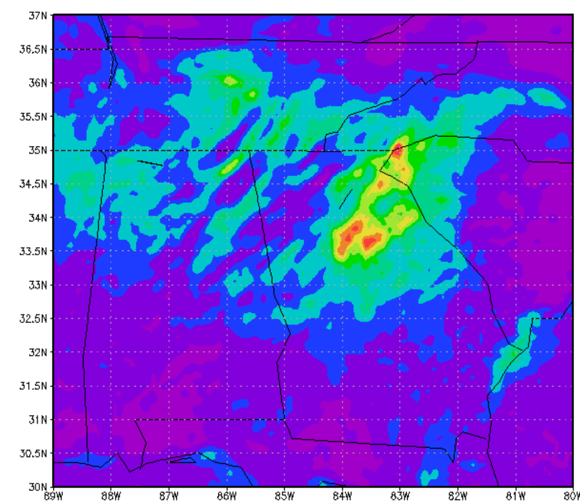
Ground-based Verification (NOAA Stage IV data)



3DVAR, no AMSR-E,TMI (WRF-GSI)



EDAS, with AMSR-E, TMI (WRF-EDAS)



Assimilation of precipitation-affected radiance improves short-term precipitation forecasts, in spatial pattern and intensity

Summary:

- A cloud-resolving WRF ensemble data assimilation system has been developed to downscale satellite precipitation observations

- Hydrometeors are included in analysis control variables to link with observed radiances, also to provide a means to examine their error characteristics relevant to precipitation assimilation

- The ensemble assimilation approach provides state-dependent background covariance that is beneficial for radiance assimilation in precipitation regions

Near Future Work:

- bias correction and observation error estimation for precipitation radiances

- statistical surface rain verification and validation

- many questions and flaws remain, we will keep on exploring and improving.